Design of a Fuzzy Traffic Controller for ATM Networks

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***Abstract*— This paper presents the design of a fuzzy traffic controller that simultaneously manages congestion control and call admission control for asynchronous transfer mode (ATM) networks. The fuzzy traffic controller is a fuzzy implementation of the two-threshold congestion control method and the equivalent capacity admission control method extensively studied in the literature. It is an improved, intelligent implementation that not only utilizes the mathematical formulation of classical control but also mimics the expert knowledge of traffic control. We appropriately choose input linguistic variables of the fuzzy traffic controller so that the controller is a closed-loop system with stable and robust operation. We extract knowledge of conventional control methods from numerous analytical data using a clustering technique and then use this knowledge to set parameters of the membership functions and fuzzy control rules via fuzzy set manipulation (linguistically stated but mathematically treated) with the aid of an optimization technique named genetic algorithm (GA). Simulation results show that the proposed fuzzy admission control improves system utilization by a significant 11%, while maintaining the quality of service (QoS) contract comparable with that of the conventional equivalent capacity method. The performance of the proposed fuzzy congestion control method is also 4% better than that of the conventional two-threshold congestion control method.**

I. Introduction

ASYNCHRONOUS transfer mode (ATM) is a key technology for integrating multimedia services in high-speed networks. Because these multimedia services have bursty traffic characteristics and various quality of service (QoS) and bandwidth requirements, an ATM network requires a sophisticated, real-time traffic controller that manages call admission control and congestion control, to guarantee the QoS for existing calls and to achieve high system utilization.

There are two main schemes available for call admission control in an ATM network [1]–[5]. The first applies a parametric model of the traffic being offered, either by requiring each call to provide an accurate description of its traffic behavior (via traffic parameters), or by measuring the observed traffic and fitting it to a model, and then infers the cell loss rate (and other network performance measures) from this model. Guérin *et al.* [1] proposed an equivalent capacity method for individual and multiplexed connections, based on their traffic parameters and desired QoS. Saito [2] proposed a call admission scheme by inferring the upper bound of cell loss probability from the traffic parameters specified by users. When a new connection is requested, the network examines either the required bandwidth [1] or the QoS requirements [2] to decide whether to accept the new call. The second type of call admission scheme measures the performance within the network for the call setup decision. Hiramatsu [3] proposed a neural net based call admission controller. This admission controller uses the offered traffic characteristics, QoS, and the performance measures of actual network operation to decide whether to accept or reject call set-up requests. Kamitake and Suda [4] proposed an instantaneous cell loss probability method for call admission control. A new call request is accepted only when the instantaneous cell loss rate is kept below a threshold value for longer than a predetermined period of time. To date, no call admission control mechanism has been proposed that considers these two schemes simultaneously.

Because of the unpredictable statistical fluctuations in the traffic flows of multimedia services, network congestion may still occur even though an appropriate call admission control scheme is provided [5]–[9]. In order to prevent the QoS from severely degrading during short-term congestion, an appropriate congestion control must also be provided. One approach to congestion control is via traffic smoothing. In [6], Masayuki *et al.* investigated how network performance depended on the degree of burstiness of the input traffic and observed that smoothing input traffic could reduce network congestion. Other approaches to congestion control were based on the two-threshold control method [7]–[10], within which, two threshold values were used to determine the onset and the relief of congestion, and selective discarding was performed during congestion periods.

However, all of these congestion control and call admission control schemes that utilize either buffer thresholds or capacity estimation, suffer from some fundamental limitations. Generally, it is difficult for a network to acquire complete statistics of input traffic [6]. As a result, it is not easy to accurately determine the effective thresholds or equivalent capacity in various bursty traffic flow conditions of ATM networks. The rationale and principles underlying the nature and choice of thresholds or equivalent capacity under dynamic conditions are unclear [11]. Therefore, a network is forced to make a decision based on incomplete information [6], and the decision process is full of uncertainty.

Recently, fuzzy logic systems have been widely applied to control nonlinear, time-varying, and ill-defined systems in which they can provide simple and effective solutions. A fuzzy logic controller (FLC), as shown in [12, Fig. 2],

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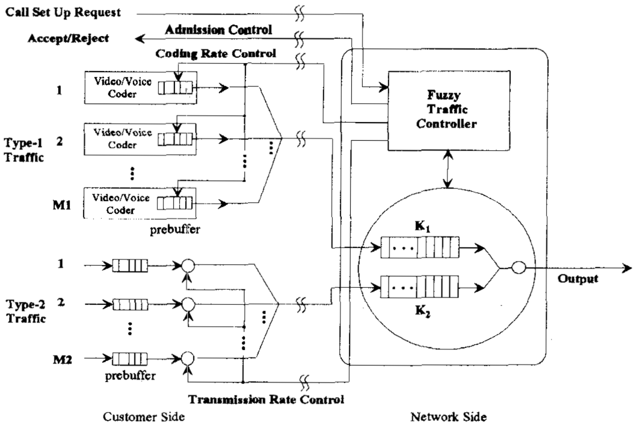

Fig. 1. The system model.

has three functional blocks: a fuzzifier, a defuzzifier, and an inference engine containing a fuzzy rule base. The fuzzifier performs the function of fuzzification that translates the value of each input linguistic variable x into fuzzy linguistic terms. These fuzzy linguistic terms are defined in a term set $T(x)$ and are specified by a set of membership functions [13]. The defuzzifier describes an output linguistic variable of the control action y by a term set $T(y)$, characterized by a set of membership functions, and adopts a defuzzification strategy to convert the linguistic terms of $T(y)$ into a nonfuzzy value that represents control action y. The term set should be determined at an appropriate level of granularity to describe the values of linguistic variables, and the number of terms in a term set is selected as a compromise between the complexity and the controlled performance. The fuzzy rule base is the control policy knowledge base, characterized by a set of linguistic statements in the form of "if–then" rules that describe the fuzzy logic relationship between the input variables x and the control action y. The inference engine embodies the decision making logic. It acquires the input linguistic terms of $T(x)$ from the fuzzifier and uses an inference method to obtain the output linguistic terms of $T(y)$. For details concerning the FLC, see [13]. This fuzzy approach can provide soft thresholds, characterize imprecise quantities, and capture a linguistic, rule-based control strategy.

Holtzman [14] examined the use of a fuzzy approach to cope with aspects of traffic uncertainty in ATM networks. Bonde and Ghosh [11] introduced fuzzy mathematics to provide flexible and high-performance solution to queue management in ATM networks. Ndousse [15] proposed a fuzzy logic implementation of the leaky bucket mechanism that used a channel utilization feedback via the QoS parameters to improve performance. This previous research indicates that the fuzzy set theory can provide a robust mathematical framework for dealing with real-world imprecision and that the fuzzy approach exhibits a soft behavior that means having a greater ability to adapt to dynamic, imprecise, and bursty environments [11]–[15].

This paper presents the design of a traffic controller that incorporates call admission control and congestion control simultaneously. The traffic controller is based on fuzzy set theory and the knowledge of experts with substantial experience in traffic control for ATM networks [1]–[11], [14]–[18]. In the fuzzy congestion controller, not only the queue length (used in the two-threshold mechanism) but also the queue-length change rate (local dynamic of the difference between arrival rate and service rate) and the cell loss probability (system performance feedback) are taken into account to indicate the occurrence of congestion. These three parameters provide much more information and, thus, a better chance of detecting the onset and relief of congestion in advance. This fuzzy congestion controller can prevent and relieve congestion as soon as possible. In the fuzzy admission controller, not only the declared traffic parameters of peak bit rate (PBR), average bit rate (ABR), and peak bit rate duration (PBRD) [1] but also the extent of network congestion and the cell loss probability [4] are employed in making call-acceptance decisions. In other words, both of the schemes for call admission control described before are employed, but with varying degrees of importance attached to each. This mixture of declared variables and network performance measures provides much more information for making call-acceptance decisions than would be available using only one set of variables.

The parameters and rules of the fuzzy traffic controller are initially set, induced from many analytical results of the two-threshold congestion control method [7] and the equivalent capacity method [1]. The parameters of the membership functions and the control rules are then further calibrated through simulations using a genetic algorithm (GA) optimization technique [19]–[21]. The proposed fuzzy traffic controller can provide robust operation under dynamic and bursty environment. A comparative study shows that the proposed fuzzy admission controller improves the system utilization by a significant 11% while keeping QoS contracts with all existing calls, comparable to the conventional equivalent capacity method in [1], and the performance of the proposed fuzzy congestion controller is 4% better than that of the conventional two-threshold control method in [7].

The organization of this paper is as follows. The functional block diagram of the fuzzy traffic controller is introduced in Section II, where the system model for an ATM network is also described. Sections III, IV, and V describe the design of the fuzzy congestion controller, the fuzzy bandwidth predictor, and the fuzzy admission controller, respectively. Section VI presents simulation results and compares the performance of the proposed controller with that of previous approaches. Concluding remarks are presented in Section VII.

II. Fuzzy Traffic Controller

The system model of an ATM network with a fuzzy traffic controller is shown in Fig. 1. The input traffic coming from the customer side is categorized into two types: real-time (type-1) and nonreal-time (type-2) traffic. Video and voice services are examples of type-1 traffic, while data services are examples of type-2 traffic. All the traffic messages, generated from sources of services on the customer side, are segmented into fixed-length packets called ATM cells and stored in the prebuffer of the customer-premises equipment (CPE) to await transmission. The network system supports two separate finite buffers with

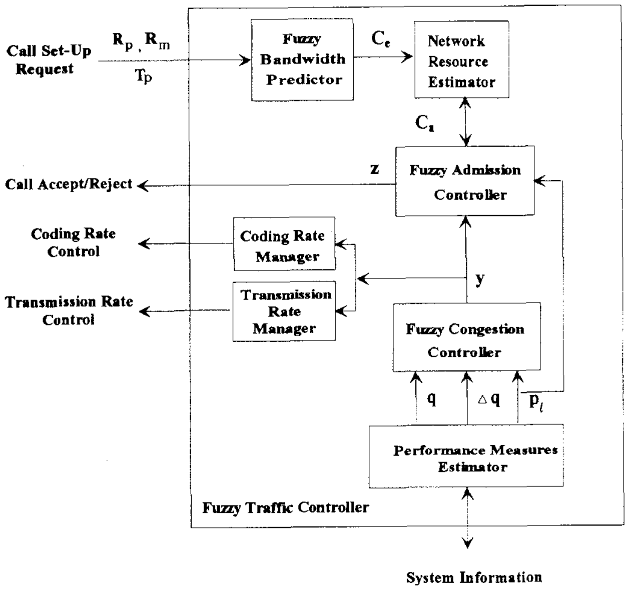

Fig. 2. Functional block diagram for the fuzzy traffic controller.

size K_i for type-i traffic, where $i = 1$ and 2. When the buffer is full, incoming cells are blocked and lost. The system reserves a portion C_r of its capacity for type-1 traffic and the remaining $(1-C_r)$ portion for type-2 traffic. When there is unused type-1 or type-2 capacity, it is used for the other type.

Figure 2 shows the functional block diagram of the fuzzy traffic controller. Its operations can briefly be described as follows. The *performance measures estimator* measures the system performance of the queue length q, the queue-length change rate Δq, and the cell-loss probabilities p_l for type-1 and type-2 traffic, and feeds these measures to the fuzzy congestion controller. The *fuzzy congestion controller* is an FLC that can prevent or relieve network congestion. As shown in Fig. 2, the fuzzy congestion controller generates a control action y according to a set of input linguistic variables of system performance measures q, Δq, p_l, and a set of built-in fuzzy control rules. These rules are predefined in a rule base constructed on the basis of expert knowledge of the two-threshold congestion control method. A negative value of y denotes that the system has a certain degree of congestion, a new call has little chance of being accepted, and the selective discarding procedure (or the transmission rate reduction procedure) for the existing type-1 (type-2) calls would be performed. A positive value of y indicates that the system is free of congestion to a certain degree, new calls have a good chance of entering the network, and existing calls can be restored to their original rates. The *coding rate manager* sends a coding rate control command to the type-1 traffic sources to perform a selective discard or restoration function for type-1 traffic at the prebuffer according to the value of control action y. The *transmission rate manager* sends a transmission rate control command to the type-2 traffic sources to reduce or restore the transmission rate for type-2 traffic according to the value of control action y. The *fuzzy baandwidth predictor* predicts the equivalent capacity C_e required for a new call from the traffic parameters PRO, ABR, and PBRD, denoted by R_p, R_m, and T_p, respectively. It is an FLC, where a set of fuzzy rules constructed from knowledge about the equivalent capacity assignment for a new call gives an appropriate estimation of the required equivalent capacity C_e. The *network resource estimator* performs the accounting for system-resource usage. When a new call is accepted by the fuzzy admission controller, the required equivalent capacity C_e, which is virtually reserved for the new customer, is subtracted from the total capacity C_a. On the other hand, when a connected call ends its service, its C_e is added to C_a. C_a is initially set to one. The *fuzzy admission controller* is also an FLC, one that deals with the call admission control procedure. A call accept/reject control action z is determined by the linguistic variables p_l from the performance measures estimator, y from the fuzzy congestion controller, and C_a from the network resource estimator. A set of fuzzy control rules is built into this block to make call admission decisions. The signal z is sent back to the new customer on the customer side to indicate acceptance or rejection of the new call request.

The fuzzy traffic controller simultaneously handles congestion control and call admission control. Via properly chosen input variables, it is a closed-loop control system capable of adjusting itself to provide stable, robust operation and avert congestion not only at the cell level but also at the call level.

III. Fuzzy Congestion Controller

In addition to the queue length q, which the fuzzy queue management scheme in [11] uses as an input linguistic variable, the proposed fuzzy congestion controller further selects the queue-length change rate Δq that can effectively describe the local dynamic of the difference between the arrival rate and the service rate, as another input linguistic variable. Also, because control theory suggests that a system with feedback has a greater ability to adapt to dynamic conditions, the fuzzy congestion controller employs the cell loss probability p_l as a third input linguistic variable. The output linguistic variable is the congestion control action y.

On the basis of existing knowledge of congestion control [5], [11], the terms "empty" and "full" are used to describe the queue length and, thus, the term set for the queue length is defined as $T(q) = \{\text{Empty}\,(E), \text{Full}\,(F)\}$. The terms used to describe the queue-length change rate are "positive" and "negative," and, thus, the term set for the queue-length change rate is defined as $T(\Delta q) = \{\text{Negative}\,(N), \text{Positive}\,(P)\}$. The terms used to describe the cell loss probability, which is one of the dominant QoS requirements, are "satisfied" and "not satisfied" and, thus, the term set for the cell loss probability is defined as $T(p_l) = \{\text{Satisfied}\,(S), \text{Not Satisfied}\,(NS)\}$. On the other hand, in order to provide a soft congestion control, not only the control action of "no change" is considered, but also the two-threshold control actions of "increase" and "decrease" are further divided into four levels, and the term set for the output control action is defined as $T(y) = \{$Decrease More (DM), Decrease Slightly (DS), No Change (NC), Increase Slightly (IS), Increase More $(IM)\}$.

The membership functions for terms in the term set should be defined with the proper shape and position. Usually, a

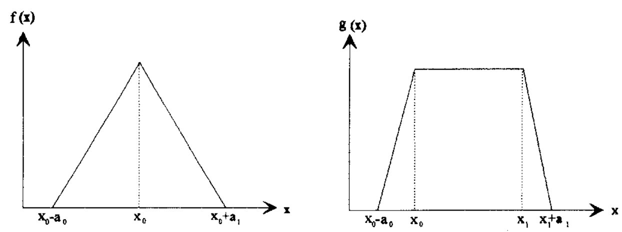

Fig. 3. Definitions for functions $f(\cdot)$ and $g(\cdot)$.

triangular function $f(x;\, x_0,\, a_0,\, a_1)$ or a trapezoidal function $g(x;\, x_0,\, x_1,\, a_0,\, a_1)$ is chosen as the membership function because these functions are suitable for real-time operation [13]. As shown in Fig. 3, $f(x;\, x_0,\, a_0,\, a_1)$ and $g(x;\, x_0,\, x_1,\, a_0,\, a_1)$ are given by

$$f(x;\, x_0,\, a_0,\, a_1) = \begin{cases} \dfrac{x - x_0}{a_0} + 1 & \text{for } x_0 - a_0 < x \le x_0 \\ \dfrac{x_0 - x}{a_1} + 1 & \text{for } x_0 < x \le x_0 + a_1 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$g(x;\, x_0,\, x_1,\, a_0,\, a_1) = \begin{cases} \dfrac{x - x_0}{a_0} + 1 & \text{for } x_0 - a_0 < x \le x_0 \\ 1 & \text{for } x_0 < x \le x_1 \\ \dfrac{x_1 - x}{a_1} + 1 & \text{for } x_1 < x \le x_1 + a_1 \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

where x_0 in $f(\cdot)$ is the center of the triangular function; x_0 (x_1) in $g(\cdot)$ is the left (right) edge of the trapezoidal function; and a_0 (a_1) is the left (right) width of the triangular or the trapezoidal function.

Let $\mu_E(q)$ and $\mu_F(q)$ denote the membership functions for E and F in $T(q)$, respectively, and let $\mu_E(q)$ and $\mu_F(q)$ be

$$\mu_E(q) = g(q;\, 0,\, E_e,\, 0,\, E_w) \tag{3}$$

$$\mu_F(q) = g(q;\, F_e,\, K_i,\, F_w,\, 0). \tag{4}$$

The two-threshold congestion control method [7]–[10] considers the system congested if the queue length exceeds the high threshold and uncongested if the queue length drops below the low threshold. As shown in Fig. 4(a), the maximum value of q would be the total buffer size for type-i traffic K_i, the edges E_e and F_e could be the low and high thresholds in the two-threshold control method, and $E_w = F_w$ could be the difference between the two thresholds.

Similarly, let $\mu_N(\Delta q)$ and $\mu_P(\Delta q)$ denote the membership functions for the terms N and P in $T(\Delta q)$, respectively, and define $\mu_N(\Delta q)$ and $\mu_P(\Delta q)$ as

$$\mu_N(\Delta q) = g(\Delta q;\, -K_i,\, N_e,\, 0,\, N_w) \tag{5}$$

$$\mu_P(\Delta q) = g(\Delta q;\, P_e,\, K_i,\, P_w,\, 0). \tag{6}$$

As shown in Fig. 4(b), the respective maximum possible "negative" and "positive" queue-length change rate would be $-K_i$ and K_i, P_e would be the queue-length change rate during congestion periods, and N_e would be the queue-length change rate during congestion-free periods, and let $P_w = N_w = P_e - N_e$. These parameters could be optimally determined via GA by simulation [21].

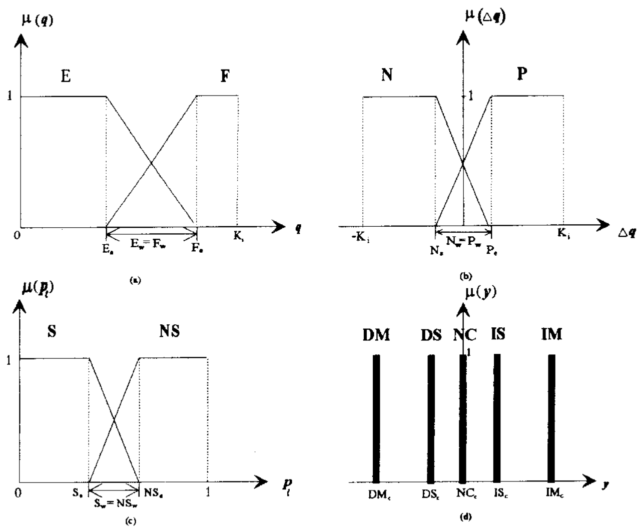

Fig. 4. The membership function of the term set (a) $T(q)$, (b) $T(\Delta q)$, (c) $T(p)$, and (d) $T(y)$.

Let $\mu_S(p_l)$ and $\mu_{NS}(p_l)$ denote the membership functions of the terms S and NS in $T(p_l)$, respectively, and let $\mu_S(p_l)$ and $\mu_{NS}(p_l)$ be

$$\mu_S(p_l) = g(p_l;\, 0,\, S_e,\, 0,\, S_w) \tag{7}$$

$$\mu_{NS}(p_l) = g(p_l;\, NS_e,\, 1,\, NS_w,\, 0). \tag{8}$$

As shown in Fig. 4(c), NS_e would be set to be the QoS requirement, S_e would be set to be a fraction of the QoS requirement, and let $S_w = NS_w = NS_e - S_e$. As a result, there exists a safety margin between NS_e and S_e provided to tolerate the dynamic behavior of the cell loss probability and guarantee the QoS requirement.

The membership functions associated with the terms DM, DS, NC, IS, and IM in $T(y)$ are denoted by $\mu_{DM}(y)$, $\mu_{DS}(y)$, $\mu_{NC}(y)$, $\mu_{IS}(y)$, and $\mu_{IM}(y)$, respectively, which are given by

$$\mu_{DM}(y) = f(y;\, DM_c,\, 0,\, 0) \tag{9}$$

$$\mu_{DS}(y) = f(y;\, DS_c,\, 0,\, 0) \tag{10}$$

$$\mu_{NC}(y) = f(y;\, NC_c,\, 0,\, 0) \tag{11}$$

$$\mu_{IS}(y) = f(y;\, IS_c,\, 0,\, 0) \tag{12}$$

$$\mu_{IM}(y) = f(y;\, IM_c,\, 0,\, 0). \tag{13}$$

As shown in Fig. 4(d), NC_c would usually be set to be zero, the value of DM_c would be set to be the maximum percentage of cells that are prohibited from entering the network or can be discarded during congestion periods, and DS_c is set to be equal to a value between DM_c and NC_c. As in the choice of the step size for adaptive differential pulse code modulation (ADPCM), a small value of DS_c is essential for accurate control while a large value of DS_c provides greater adaptability. IM_c and IS_c are set to be the positive values of DM_c and DS_c, respectively, for symmetry.

According to fuzzy set theory, the fuzzy rule base forms a fuzzy set with dimensions $|T(q)| \times |T(\Delta q)| \times |T(p)|$ [$|T(x)|$ denotes the number of terms in $T(x)$]. We initially set a total

TABLE I-A
RULE STRUCTURE FOR THE FUZZY CONGESTION CONTROLLER: THE INITIAL RULE STRUCTURE

Rule	q	Δq	p_l	y	Rule	q	Δq	p_l	y
1	E	N	S	IM	5	F	N	S	DM
2	E	N	NS	IM	6	F	N	NS	DM
3	E	P	S	IM	7	F	P	S	DM
4	E	P	NS	IM	8	F	P	NS	DM

TABLE I-B
RULE STRUCTURE FOR THE FUZZY CONGESTION CONTROLLER: THE OPTIMAL STRUCTURE

Rule	q	Δq	p_l	y	Rule	q	Δq	p_l	y
1	E	N	S	IM	5	F	N	S	IM
2	E	N	NS	IM	6	F	N	NS	IM
3	E	P	S	IS	7	F	P	S	DS
4	E	P	NS	IM	8	F	P	NS	NC

of eight inference rules in the fuzzy rule base by utilizing only the two-threshold congestion control method. The initial rule structure is shown in Table I-A. The rule structure takes the form shown because the two-threshold congestion control method can be linguistically stated as "if the queue length is full, then reduce the source rate at the maximum possible amount; if the queue length is empty, then restore the source rate at the maximum possible amount." In terms of a fuzzy logic description, the above statement would be "if q is F, then y is DM; if q is E, then y is IM." There is no prior information about the usage of "y is IS," "y is NC," and "y is DS" in response to the information obtained from Δq and p_l. Thus, the terms IS, NC, and DS are not contained in the initial rule structure. We further optimized the initial rule structure via simulation with a GA to obtain the optimal rule structure shown in Table I-B. The control action "decrease more" is eliminated from the rule structure after optimization because the fuzzy congestion controller indicates the occurrence of congestion in advance and, thus, the soft control "decrease slightly" is sufficient.

The proposed fuzzy congestion controller adopts the max–min inference method [13] for the inference engine because it is designed for real-time operation. Fig. 5 shows an example of the max–min inference method for the fuzzy congestion controller, where rules 1, 2, 4, 5, and 6, which have the same control action, "y is IM," are depicted. In this figure, we assume that the performance measure estimator measures q, Δq, and p_l and yields q_0, Δq_0, and p_{l0}. The membership values of q_0, Δq_0, and p_{l0} corresponding to the premise of rule 1 (for example) shown in Table I—q is empty, Δq is negative, and p_l is safe—are given by $\mu_E(q_0)$, $\mu_N(\Delta q_0)$, and $\mu_S(p_{l0})$, respectively. Applying the min operator, we can obtain the membership value of the control action $y = IM$

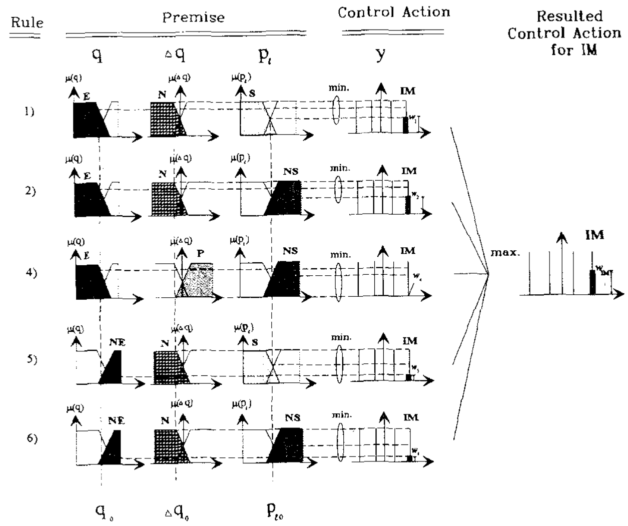

Fig. 5. The max–min inference method.

of rule 1, denoted by w_1, by

$$w_1 = \min\left[\mu_E(q_0),\, \mu_N(\Delta q_0),\, \mu_S(p_{l0})\right] \cdot \mu_{IM}(y = IM_c) \tag{14}$$

where IM_c is the center of the membership function $\mu_{IM}(y)$ defined in (13). The membership values of rules 2, 4, 5, and 6, denoted by w_2, w_4, w_5, and w_6, respectively, can be obtained in the same manner. Subsequently, applying the max operator yields the overall membership value of the control action $y = IM$, denoted by w_{IM}, as follows:

$$w_{IM} = \max(w_1, w_2, w_4, w_5, w_6). \tag{15}$$

The overall membership values of the control actions IS, NC, DS, and DM, denoted by w_{IS}, w_{NC}, w_{DS}, and w_{DM}, respectively, can be calculated in a similar way.

The fuzzy congestion controller also uses Tsukamoto's defuzzification method for the defuzzifier [13] because of its simplicity in computation. This defuzzification method obtains a crisp value y_0 of the control action y by combining w_{IM}, w_{IS}, w_{NC}, w_{DS}, and w_{DM} (16), shown at the bottom of the page. On the basis of crisp value y_0, the coding rate manager (the transmission rate manager) sends a coding (transmission) rate control command to throttle the incoming traffic. Less significant cells of type-1 traffic are then selectively discarded, and the transmission rate of type-2 traffic is then altered. The max–min inference method and Tsukamoto's defuzzification method are also applied in the design of the fuzzy bandwidth predictor and the fuzzy admission controller, which will be described in the next two sections.

$$y_0 = \frac{(IM_c \cdot w_{IM} + IS_c \cdot w_{IS} + NC_c \cdot w_{NC} + DS_c \cdot w_{DS} + DM_c \cdot w_{DM})}{(w_{IM} + w_{IS} + w_{NC} + w_{DS} + w_{DM})} \tag{16}$$

TABLE II
RULE STRUCTURE FOR THE FUZZY BANDWIDTH PREDICTOR

Rule	R_p	R_m	T_p	C_e	Rule	R_p	R_m	T_p	C_e	Rule	R_p	R_m	T_p	C_e
1	S	Lo	Sh	C_1	7	M	Lo	Sh	C_1	13	L	Lo	Sh	C_4
2	S	Lo	Me	C_2	8	M	Lo	Me	C_3	14	L	Lo	Me	C_6
3	S	Lo	Lg	C_5	9	M	Lo	Lg	C_6	15	L	Lo	Lg	C_6
4	S	Hi	Sh	C_1	10	M	Hi	Sh	C_1	16	L	Hi	Sh	C_3
5	S	Hi	Me	C_1	11	M	Hi	Me	C_2	17	L	Hi	Me	C_5
6	S	Hi	Lg	C_4	12	M	Hi	Lg	C_5	18	L	Hi	Lg	C_6

IV. FUZZY BANDWIDTH PREDICTOR

The fuzzy bandwidth predictor is a fuzzy implementation of the equivalent capacity method proposed by Guérin *et al.* [1]. In accordance with expert knowledge [1], [5], [10], the fuzzy bandwidth predictor selects R_p, R_m, and T_p as the input linguistic (traffic) variables and uses the estimated equivalent capacity, denoted by C_e, as the output linguistic variable.

In order to extract knowledge of the equivalent capacity method, a total of 10^5 items of numerical data were acquired by extensively calculating the equivalent capacity in [1, (2)] for different combinations of R_p, R_m, and T_p. The numerical results show that three terms are good enough for R_p, two terms are good enough for R_m, and three terms are needed to describe T_p. Accordingly, the term sets for R_p, R_m, and T_p are defined as $T(R_p) = \{\text{Small}\,(S), \text{ Medium }(M), \text{ Large }(L)\}$, $T(R_m = \{\text{Low}\,(Lo), \text{ High }(Hi)\}$, and $T(T_p) = \{\text{Short}\,(Sh),$ Medium (Me), Long $(Lg)\}$, respectively. Also, the estimated equivalent capacity for a call should fall between its R_m and R_p. The fuzzy bandwidth predictor proposed in this paper divides the range between R_m and R_p into six quantization levels. Let C_i $(i = 1, \cdots, 6)$ denote the ith level of the capacity estimation and define the term set for the estimated capacity as $T(C_e) = \{C_1, C_2, C_3, C_4, C_5, C_6\}$.

The membership functions for $T(R_p)$, $T(R_m)$, and $T(T_p)$ are defined as

$$\mu_S(R_p) = g[\log(R_p); \log(R_{p,\min}), S_e, 0, S_w] \tag{17}$$

$$\mu_M(R_p) = f[\log(R_p); M_c, M_{w0}, M_{w1}] \tag{18}$$

$$\mu_L(R_p) = g[\log(R_p); L_e, \log(R_{p,\max}), L_w, 0] \tag{19}$$

$$\mu_{Lo}(R_m) = g\left(\frac{R_m}{R_p}; 0, Lo_e, 0, Lo_w\right) \tag{20}$$

$$\mu_{Hi}(R_m) = g\left(\frac{R_m}{R_p}; Hi_e, 1, Hi_w, 0\right) \tag{21}$$

$$\mu_{Sh}(T_p) = g[\log(T_p); \log(T_{p,\min}), Sh_e, 0, Sh_w] \tag{22}$$

$$\mu_{Me}(T_p) = f[\log(T_p); Me_c, Me_{w0}, Me_{w1}] \tag{23}$$

$$\mu_{Lg}(T_p) = g[\log(T_p); Lg_e, \log(T_{p,\min}), Lg_w, 0] \tag{24}$$

where $R_{p,\min}$, $R_{p,\max}$, $T_{p,\min}$, and $T_{p,\max}$ are the minimum and maximum possible values for R_p and T_p, respectively. In order to accommodate a wide variety of different traffic sources, the logarithmic function is employed for input linguistic variables R_p and T_p based on the analytical results of the equivalent capacity method. The membership functions for the terms in $T(R_m)$ are divided by R_p to use as an indicator of burstiness [5]. As stated above, the knowledge for the fuzzy bandwidth predictor is obtained by extensively computing the equivalent capacity [1, (2)] for different traffic sources. According to the numerical results, (S_e, M_c, L_e) in (17)–(19), (Lo_e, Hi_e) in (20) and (21), and (Sh_e, Me_c, Lg_e) in (22)–(24) can be set to be the proper boundary values used to characterize R_p, R_m/R_p, and T_p, respectively. Also, $S_w = M_{w0} = M_c - S_e$, $M_{w1} = L_w = L_e - M_c$, $Lo_w = Hi_w = Hi_e - Lo_e$, $Sh_w = Me_{w0} = Me_c - Sh_e$, and $Me_{w1} = Lg_w = Lg_e - Me_c$ can be set accordingly and then fine-tuned.

For the membership functions of the predicted capacity, the six levels mentioned above are equally spaced. The membership functions for $T(C_e)$ are defined as

$$\mu_{C_1}(C_e) = f(C_e; C_{1,c}, 0, 0), \tag{25}$$

$$\mu_{C_2}(C_e) = f(C_e; C_{2,c}, 0, 0) \tag{26}$$

$$\mu_{C_3}(C_e) = f(C_e; C_{3,c}, 0, 0) \tag{27}$$

$$\mu_{C_4}(C_e) = f(C_e; C_{4,c}, 0, 0) \tag{28}$$

$$\mu_{C_5}(C_e) = f(C_e; C_{5,c}, 0, 0) \tag{29}$$

$$\mu_{C_6}(C_e) = f(C_e; C_{6,c}, 0, 0) \tag{30}$$

where $C_{1,c} = R_m$ and $C_{i,c} = C_{i-1,c} + (R_p - R_m)/5$, $i = 2, \cdots, 6$.

The fuzzy control rules for the fuzzy bandwidth predictor are given in Table II, induced from numerous numerical data. As an illustration, C_e for rule 1 was determined in the following. We selected data of R_p, R_m, and T_p such that $\mu_S(R_p) = 1$, $\mu_{Lo}(R_m) = 1$, and $\mu_{Sh}(T_p) = 1$. The calculated equivalent capacity of each data of R_p, R_m, and T_p was quantized into a level of $\{C_1, C_2, C_3, C_4, C_5, C_6\}$. Consequently, the estimated equivalent capacity C_e of rule 1 was determined via a majority vote. In the case of rule 1, C_1 occurred most frequently, so it was chosen as C_e. The other rules were obtained by applying a similar procedure.

V. FUZZY ADMISSION CONTROLLER

Unlike the equivalent capacity admission control method proposed in [1], which uses only the available capacity C_a as a variable for call set-up decisions, the fuzzy admission controller considers the network congestion control action y, which contains information on congestion within the network, and the cell loss probability p_l, which is used as the channel utilization feedback [3], as two further input linguistic variables. The accept/reject decision z is the output linguistic variable.

In the call admission control methods proposed in the literature [1], [5], [10], the terms used to describe available

TABLE III
RULE STRUCTURE FOR THE FUZZY ADMISSION CONTROLLER

Rule	p_l	y	C_a	z	Rule	p_l	y	C_a	z
1	S	P	E	A	5	NS	P	E	WR
2	S	P	NE	WA	6	NS	P	NE	R
3	S	N	E	WA	7	NS	N	E	R
4	S	N	NE	WR	8	NS	N	NE	R

capacity for a new call are "Not Enough" and "Enough," and, thus, the term set for the available capacity is defined as $T(C_a) = $ Not Enough (NE), Enough $(E)\}$. The system is in either a congestion state (y is negative) or congestion-free state (y is positive), and the term set for the congestion control action is defined as $T(y) = \{$Negative (N), Positive $(P)\}$. The term set for the cell loss probability is defined the same as $T(p_l)$ in the fuzzy congestion controller. In order to provide a soft admission decision, not only "accept" and "reject" but also "weak accept" and "weak reject" are employed to describe the accept/reject decision. Thus, the term set of the output linguistic variable is defined as $T(z) = \{$Accept (A), Weak Accept (WA), Weak Reject (WR), Reject $(R)\}$.

The membership functions for $T(p_l)$ have already been defined in (7) and (8). The membership functions for $T(C_a)$ and $T(y)$ are defined as

$$\mu_{NE}(C_a) = g(C_a;\, 0,\, NE_e,\, 0,\, NE_w), \tag{31}$$
$$\mu_E(C_a) = g(C_a;\, E_e,\, C,\, E_w,\, 0) \tag{32}$$
$$\mu_N(y) = g(y;\, -y_{\max},\, N_e,\, 0,\, N_w) \tag{33}$$
$$\mu_P(y) = g(y;\, P_e,\, y_{\max},\, P_w,\, 0) \tag{34}$$

where C denotes the total network capacity provided for type-i traffic [C is C_r for type-1 traffic and is $(1 - C_r)$ for type-2 traffic]; $y_{\max}$ denotes the maximum percentage of cells that are prohibited from entering the network; E_e is designed to be a fraction of C and is used to tolerate the estimation uncertainty resulting from the dynamic traffic characteristics as well as the fuzzy implementation of the equivalent capacity method; NE_e is smaller than E_e and is used to indicate an emergency due to lack of capacity; and N_e and P_e are values properly set by monitoring the control action y of the fuzzy congestion controller during congestion and congestion-free periods, respectively. N_e and P_e are calibrated via simulation. In the simulations, an amount of short-term congestion was stimulated by overloading the system. The values of control action y were sampled and clustered according to congestion or congestion-free states. We set N_e and P_e to be the mean values of the control action y in the congestion and the congestion-free states.

Similarly, the membership functions for $T(z)$ are defined as

$$\mu_R(z) = f(z;\, R_c,\, 0,\, 0) \tag{35}$$
$$\mu_{WR}(z) = f(z;\, WR_c,\, 0,\, 0, \tag{36}$$
$$\mu_{WA}(z) = f(z;\, WA_c,\, 0,\, 0) \tag{37}$$
$$\mu_A(z) = f(z;\, A_c,\, 0,\, 0). \tag{38}$$

A new call request can be accepted if the output of the fuzzy admission controller z is greater than an acceptance threshold z_a, $R_c \le z_a \le A_c$. Without loss of generality, $R_c = 0$, $A_c = 1$, and let $WR_c = (R_c + z_a)/2$, $WA_c = (A_c + z_a)/2$.

The order of significance of the input linguistic variables for the call admission controller would be the cell loss probability p_l, the congestion control action y, and then the available system capacity C_a. The fuzzy admission control rules are designed in Table III. A new call will have no chance of entering the network and will be rejected if the cell loss probability is not satisfied ($p_l = NS$), except that a new call will be weakly rejected to improve the network utilization when the network is congestion-free ($y = P$) and has enough capacity ($C_a = E$). On the other hand, a new call has a good chance of entering the network and will be accepted or weakly accepted if the cell loss probability is satisfied ($p_l = S$), except that a new call will be weakly rejected if the network is experiencing congestion ($y = N$) and the available capacity is insufficient ($C_a = NE$).

VI. SIMULATION RESULTS

The cell arrival processes of all service traffic in the simulations were as follows. The cell generation process for a video coder was assumed to have two motion states: the low motion state for the rate of interframe coding, and the high motion state for the rate of intraframe coding [22]. The rate of intraframe coding was further divided into two parts: the first part had the same rate as the interframe coding and the second part, called difference coding, was the difference rate between intraframe coding and interframe coding. The interframe coding and the difference coding were both modeled as discrete-state Markov-modulated Bernoulli processes (MMBP) with basic rate A_r and A_a [23]. Let $\lambda_a(t)$, $\lambda_r(t)$, and $\lambda'_a(t)$ denote the cell generation rate for intraframe coding, interframe coding, and difference coding at time t, respectively, from the video coder. Clearly, $\lambda_a(t) = \lambda_r(t) + \lambda'_a(t)$. The process of $\lambda_r(t)$ is an $(M_r + 1)$-state birth–death Markov process. The state-transition diagram for $\lambda_r(t)$ uses the label $m_r A_r$ to indicate a state of the cell generation rate of interframe coding and the labels $(M_r - m_r)\gamma$ and $m_r\omega$ to denote the transition probabilities from state $m_r A_r$ to state $(m_r + 1)A_r$ and from state $m_r A_r$ to state $(m_r - 1)A_r$, respectively. Similarly, the process for $\lambda'_a(t)$ is an $(M_a + 1)$-state birth–death Markov process. The state-transition diagram for $\lambda'_a(t)$ uses the label $m_a A_a$ to indicate a state of the additional cell generation rate due to intraframe coding and the labels $(M_a - m_a)\phi$ and $m_a\psi$ to denote the transition probability from state $m_a A_a$ to state $(m_a + 1)A_a$ and from state $m_a A_a$ to state $(m_a - 1)A_a$, respectively. The video source will alternate between interframe and intraframe, depending on the video source activity factor. There is a transition rate c in the interframe state and a transition rate d in the intraframe state. The values of γ, ω, M_r, A_r, ϕ, ψ, M_a, A_a, c, and d can be obtained from the traffic variables of R_p, R_m, and T_p [5], [10]. Details about the state-transition diagrams of the source models described below can be found in [24, Fig. 2].

The cell generation process for a voice call was modeled by an interrupted Bernoulli process (IBP) [5], [7]. During the ON (talkspurt) state, voice cells were generated with rate A_v;

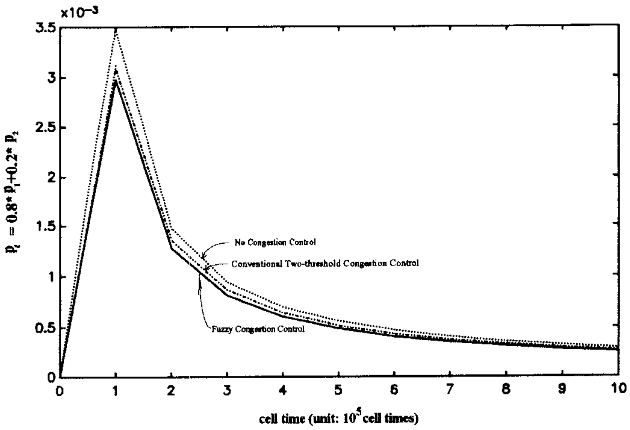

Fig. 6. The cell loss probability of an ATM network for different implementations of congestion control schemes.

during the OFF (silence) state, no cells were generated. A voice source had a transition rate α in the OFF state and a transition rate β in the ON state.

The data sources included high-bit-rate and low-bit-rate data services, and the generation of high-bit-rate data cells and low-bit-rate data cells was characterized by Bernoulli processes with rates θ_1 and θ_2, respectively. Also, the distributions of the holding times for video, voice, high-bit-rate data, and low-bit-rate data were assumed to be exponentially distributed.

In the simulations, the buffer sizes for type-1 and type-2 traffic were given by $K_1 = K_2 = 100$ cells and the portion C_r of the system capacity reserved for type-1 traffic was assumed to be 0.8. For the arrival process of a video source, it was assumed that $R_p = 3.31 \times 10^{-2}$, $R_m = 1.10 \times 10^{-2}$, and $T_p = 0.5$ s, which give $M_r = M_a = 20$, $A_r = 1.34 \times 10^{-3}$, $A_a = 3.15 \times 10^{-4}$, $\gamma = 3.77 \times 10^{-6}$, $\omega = 5.65 \times 10^{-6}$, $\phi = \psi = 2.83 \times 10^{-5}$, $c = 5.65 \times 10^{-6}$, and $d = 5.09 \times 10^{-5}$. For the arrival process of a voice source, it was assumed that $R_p = 4.71 \times 10^{-4}$, $R_m = 2.12 \times 10^{-4}$, and $T_p = 1.35$ s, which give $A_v = 4.71 \times 10^{-4}$, $\alpha = 1.71 \times 10^{-6}$, and $\beta = 2.09 \times 10^{-6}$. For high-bit-rate data sources, it was assumed that $R_p = 7.36 \times 10^{-2}$, $R_m = 7.36 \times 10^{-3}$, and $T_p = 3.14 \times 10^{-2}$ s, which give $\theta_1 = 0.1$, and for low-bit-rate data sources, it was assumed that $R_p = 3.68 \times 10^{-2}$, $R_m = 7.36 \times 10^{-4}$, and $T_p = 2.88 \times 10^{-2}$ s, which give $\theta_2 = 0.02$. The mean holding time was 60 min. for a video service, 3 min. for a voice service, and 18 s for both high and low-bit-rate data service. Note that the values of R_p and R_m are normalized by the total network capacity.

We define the cell loss probability p_l as

$$p_l = \zeta p_1 + (1 - \zeta) p_2 \tag{39}$$

where p_i is the cell loss probability of type-i traffic, $i = 1$ or 2, and ζ is a weighting factor used to distinguish between losses of these two types of traffic. p_l is an overall cell loss probability. Also, two kinds of cell loss probability for type-i traffic were considered: the source loss probability due to selective discarding at the customer side $p_{s,i}$ and the node loss probability due to blocking at the network side $p_{n,i}$; p_i is defined as

$$p_i = \kappa p_{s,i} + p_{n,i}, \quad i = 1, 2 \tag{40}$$

where κ is used to indicate the significance of the node loss over the source loss. $\zeta = 0.8$ was assumed because the lost cells of type-2 traffic can be recovered by retransmission; $\kappa = 0.8$ was assumed because selectively discarding cells at the source should have less effect on information retrieval than blocking cells at the node.

From the knowledge of the two-threshold congestion control method and the QoS requirement of 10^{-5} cell loss probability, the parameters of the membership functions for input linguistic variables in fuzzy congestion controller were selected as follows: $E_e = 75$, $F_e = 90$, and $E_w = F_w = 15$ for $\mu_E(q)$ and $\mu_F(q)$ in (3) and (4); $N_e = -1$, $P_e = +1$, and $N_w = P_w = 2$ for $\mu_N(\Delta q)$ and $\mu_P(\Delta q)$ in (7) and (8); and $S_e = 5 \times 10^{-6}$, $NS_e = 1 \times 10^{-5}$, and $S_w = NS_w = 5 \times 10^{-6}$ for $\mu_S(p_l)$ and $\mu_{NS}(p_l)$ in (7) and (8). Also, the parameters of the membership functions for output linguistic variables were given by $DM_c = -0.2$, $DS_c = -0.2/3$, $NC_c = 0$, $IS_c = 0.2/3$, and $IM_c = 0.2$ in (9)–(13).

The rule structure of the fuzzy congestion controller was optimized by using a GA, mentioned in Section III. The rule was coded into a binary string of genes and GA_{UCSD} 1.4 [20] was used for the simulations. The cell loss probability p_l defined in (39) was used as the cost function for the GA. A short period of congestion was stimulated by overloading the system and the optimal structure was obtained in Table I-B.

Fig. 6 shows the overall cell loss probability p_l for the schemes of "no congestion control," "conventional two-threshold congestion control," and "fuzzy congestion control," where the network was congested at around 1×10^5 cell times, after which, it entered a normal (congestion-free) state. The cell time was defined as the duration needed to transmit an ATM cell. It was found that the performance of the fuzzy congestion controller was about 4% better than that of the conventional two-threshold control method and about 15% better than that of no control. This superior performance was obtained because the fuzzy congestion controller utilizes much more information than a conventional controller, so it can indicate the occurrence of congestion in advance and provide a soft and accurate control during congestion periods.

For the fuzzy bandwidth predictor, we utilized the analytical results of the equivalent capacity method and mimicked expert knowledge of capacity estimation to appropriately set the parameters of the membership functions. For $\mu_S(R_p)$, $\mu_M(R_p)$, and $\mu_L(R_p)$ in (17)–(19), $S_e = -3$, $S_w = 0.9$, $M_c = -2$, $M_{w0} = M_{w1} = 1$, $L_e = -1$, $L_w = 0.9$, $R_{p,\max} = 1$, and $R_{p,\min} = 10^{-4}$; for $\mu_{Lo}(R_m)$, and $\mu_{Hi}(R_m)$ in (20), and (21), $Lo_e = 0.6$, $Lo_w = 0.15$, $Hi_e = 0.75$, and $Hi_w = 0.1$; and for $\mu_{Sh}(T_p)$, $\mu_{Me}(T_p)$, and $\mu_{Lg}(T_p)$ in (22)–(24), $Sh_e = -3$, $Sh_w = 0.7$, $Me_c = -2$, $Me_{w0} = Me_{w1} = 0.8$, $Lg_e = -1$, $Lg_w = 0.7$, and $T_{p,\max} = 100$ s, $T_{p,\min} = 10^{-9}$ s.

The fuzzy admission controller sets aside 10% of the capacity reserved as a safety margin. Thus, the parameters for $\mu_{NE}(C_a)$ and $\mu_E(C_a)$ in (31) and (32) were set as $E_e = 0.1 \times C$, $NE_e = 0.05 \times C$, and $NE_w = E_w = 0.05 \times C$. For $\mu_N(y)$ and $\mu_P(y)$ in (33) and (34), it was found that the

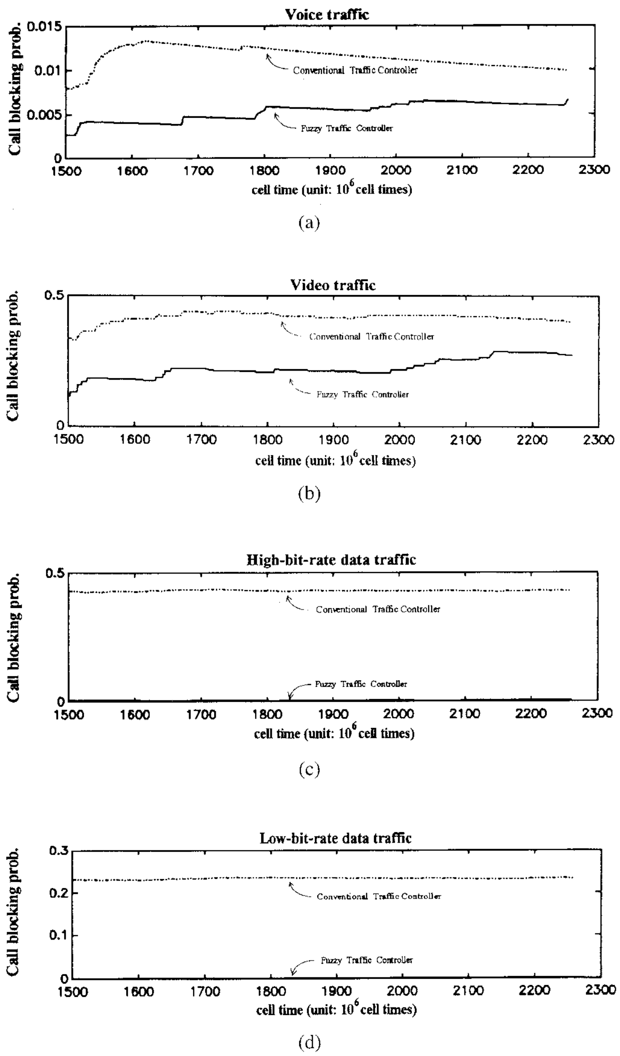

Fig. 7. The call blocking probability of (a) voice, (b) video, (c) high-bit-rate data, and (d) low-bit-rate data.

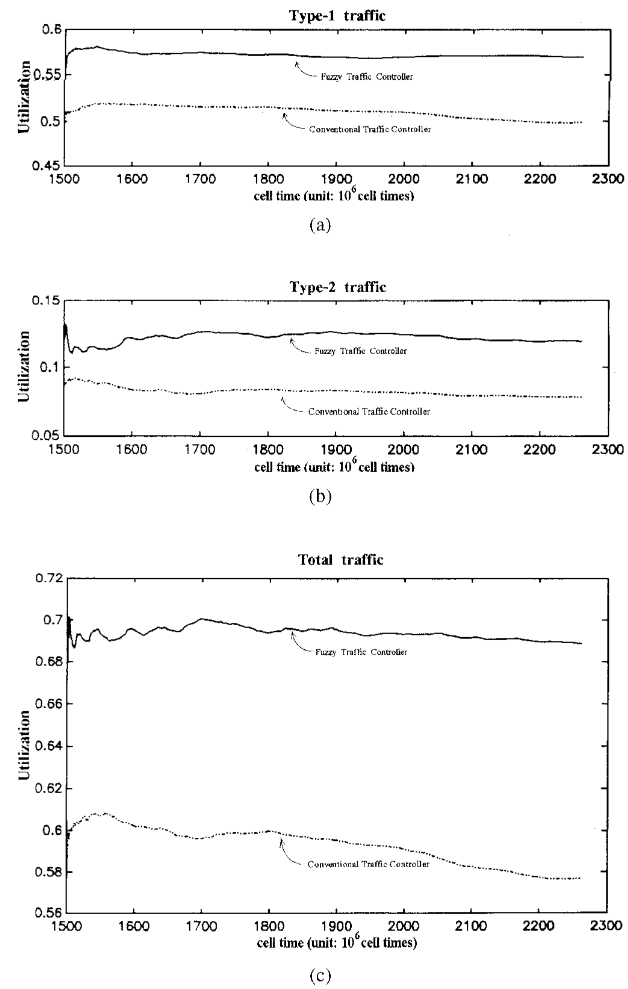

Fig. 8. The system utilization for (a) type-1 traffic, (b) type-2 traffic, and (c) total traffic.

value of y is about $-y_{\max}/5$ during congestion periods and about $y_{\max}/5$ during congestion-free periods, where $y_{\max} = IM_c = 0.2$. Thus, the parameters were set as $N_e = -y_{\max}/5$, $P_e = y_{\max}/5$, and $N_w = P_w = |P_w - N_w| = 2 \times y_{\max}/5$. For $T(z)$, the decision threshold was set to $z_a = 0.5$, which is the mean value of R_c and A_c and, thus, $WR_c = 0.25$ and $WA_c = 0.75$.

The ATM network with the proposed fuzzy traffic controller and an ATM network with a conventional traffic controller (a fixed-threshold implementation of the two-threshold congestion control method and the equivalent capacity admission control method) were simulated over a long time period. The cell loss probabilities were zero for both control schemes. Fig. 7 shows the call blocking probabilities of various services in the two ATM networks. The proposed fuzzy traffic controller provided lower call-blocking probabilities for all services than the conventional traffic controller did. Fig. 8 shows the utilization of the two ATM networks. The fuzzy traffic controller achieved better system utilization for both type-1 and type-2 traffic compared to the conventional traffic controller for the whole simulation interval in Fig. 8(a) and (b), and the overall system utilization was effectively improved by 11% in Fig. 8(c). These results were achieved because the fuzzy bandwidth predictor provides a soft and accurate estimation of the required capacity for a new call, and the fuzzy admission controller utilizes both the declared traffic parameters and the network performance parameters as input linguistic variables, thus, using much more information for decision making on call acceptance than the conventional admission controller.

VII. Conclusion

This paper has presented a design for a fuzzy traffic controller that can simultaneously manage call admission control and congestion control. The proposed design is a fuzzy logic implementation of the two-threshold congestion control method and the equivalent capacity admission control method extensively studied in the literature. It is an intelligent implementation that not only refers to the mathematical formulation of classical control but also mimics expert knowledge in traffic control. The rule structure and parameters of the membership functions of the fuzzy traffic controller are based on expert knowledge and the analytical results of the two-threshold method and the equivalent capacity method. Simulation results show that the proposed fuzzy admission control improves system utilization by 11%, while maintaining a QoS contract comparable to that of a conventional equivalent capacity method. At the same time, the performance of the proposed fuzzy congestion control method is also 4% better than that of the conventional two-threshold congestion control method during congestion periods. The fuzzy traffic controller is effective because it employs input variables that provide much more information than is used in conventional methods and because the linguistic capability of fuzzy logic handles the traffic complexity and provides soft control. Also, the fuzzy traffic controller can be implemented using fuzzy logic chips for real-time operation. The fuzzy logic approach is a promising approach for the design of traffic controllers in ATM networks.

Admittedly, there is still no clear and general technique for mapping existing knowledge on traffic control onto the design parameters of the fuzzy traffic controller. In order to develop a more general design procedure for fuzzy traffic control for ATM networks, applying the self-learning capability of a neural-net to design a fuzzy traffic controller is worthy of further study.

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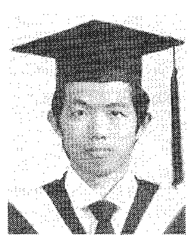

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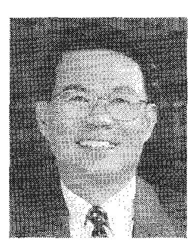

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